

# 1 Prior Predictive Distribution for $\tilde{\mu}^c$

Here, we study the prior predictive distribution of  $\tilde{\mu}^c$ , the underlying 'true' value of the parameter  $c$  for a patient with covariate vector  $\tilde{x}$ . The goal of this section is to see how our prior belief on what  $\tilde{\mu}^c$  varies depends on the hyperparameters. We first describe the log-normal distribution, because it turns out this is the distribution that  $\tilde{\mu}^c$  follows a log-normal distribution in the prior.

## 1.1 Log-Normal Distribution

A log-normal distribution is a continuous distribution defined on the open interval  $(0, \infty)$ . A random variable  $X$  follows a log-normal distribution if the transformed random variable  $\log(X)$  follows a normal distribution. An equivalent definition makes the parameterization of a log-normal distribution clear:

**Definition 1.** If  $Y \sim \text{Normal}(\mu, \sigma^2)$ , then the transformed random variable  $X = \exp(Y)$  follows a Log-Normal( $\mu, \sigma^2$ ) distribution.

Thus, a Log-Normal distributed random variable  $X$  is parameterized using the mean and standard deviation of the normal distribution that  $\log(X)$  follows.

### 1.1.1 Key Properties

The density of a Log-Normal( $\mu, \sigma^2$ ) distribution is:

$$f_X(x; \mu, \sigma^2) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{(\log(x) - \mu)^2}{2\sigma^2}\right); x > 0 \quad (1)$$

The log-normal distribution is unimodal regardless of the choice of parameters. This is suitable for our poses. There are analytical formulas for the mean and mode; the mean is  $\exp(\mu + \frac{\sigma^2}{2})$ , and the mode is  $\exp(\mu - \sigma^2)$ . Like in the case of the logit-normal distribution, neither the mean nor mode are constant as  $\sigma^2$  increases, for fixed  $\mu$ . Also, the mode and mean exhibit opposite trends. Finally, as one would expect, the variance is increasing in  $\sigma^2$ .

### 1.1.2 Log-Normality of $\tilde{\mu}^c$ in the Prior

The only hyperparameter that  $\tilde{\mu}^c$  depends on is  $c^c$ . The argument for the log-normality of  $\tilde{\mu}^c$  is exactly analogous to that for the logit-normality of  $\tilde{\mu}^a$ . The prior predictive distribution of  $\mu^c, \mu^c|c^c$ , is distributed  $g^c(\mu_{pop}^{c*} + B^c\tilde{x})$ .  $B^c \sim N(0, c^c I)$ , and so  $B^c\tilde{x} \sim N(0, \tilde{\sigma}^c)$  where  $\tilde{\sigma}^c := \tilde{x}'(c^c I)\tilde{x} = c^c \sum_{j=1}^k \tilde{x}_j^2$ . Thus  $\mu_{pop}^{c*} + B^c\tilde{x} \sim N(\mu_{pop}^{c*}, \tilde{\sigma}^c)$  and thus  $\tilde{\mu}^c \sim \text{log-normal}(\mu_{pop}^{c*}, \tilde{\sigma}^c)$